1992

Use of Landsat Imagery and Geographical Information Systems in the Assessment of Rangeland Cover and Wildlife Habitat

Mary Hunnicutt
Utah State University

USE OF LANDSAT IMAGERY AND GEOGRAPHICAL INFORMATION

SYSTEMS IN THE ASSESSMENT OF RANGELAND

COVER AND WILDLIFE HABITAT

by

Mary Hunnicutt

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Fisheries and Wildlife

Approved:

UTAH STATE UNIVERSITY
Logan, Utah

1992

ACKNOWLEDGEMENTS

I am indebted to my advisor, Dr. Winifred Kessler, for her encouragement and for her effort in editing this thesis. Dr. Fred Wagner also provided valuable editorial comments. Special thanks are extended to Drs. Douglas Ramsey and Kevin Price. Their expertise in remote sensing and geographical information systems and their enthusiasm and willingness to help me with this project were greatly appreciated. I could not have completed this project without them.

The personnel at Deseret Land and Livestock were gracious in providing access to their land, in providing me with living quarters while doing field work, and in assisting me in trapping sage grouse for this study. Rick Danvir and Shane Davis offered their assistance and companionship in the field. I will always value their friendship.

Additional field assistance for this project was provided by numerous volunteers from Utah State University, U.S.D.I. Bureau of Land Management, and Utah Division of Wildlife Resources. My husband, Dan Cohan, helped in several phases of field work, wrote computer programs for my data analysis, and assisted me with constructing figures used in my thesis.

Financial support and equipment for this project were provided, in part, by Deseret Land and Livestock, Bureau of

Land Management, Utah Division of Wildlife Resources, and from a scholarship and graduate assistantship from Utah State University.

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ABSTRACT

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by

Mary Hunnicutt, Master of Science

Utah State University, 1992

Major Professor: Dr. Winifred B. Kessler
Department: Fisheries and Wildlife

The first chapter of this thesis reviews applications of satellite remote sensing and geographical information systems (GIS) in wildlife studies. The simpler uses of remote sensing are for habitat mapping, often using satellite imagery classified for other natural resources. More sophisticated applications incorporate remotely sensed data into a GIS for the digital manipulation of data planes. The most advanced applications are those which use remote sensing and GIS in models predicting habitat quality or population levels.

The second chapter reports how brightness values of six Landsat Thematic Mapper (TM) bands were used in multiple linear regressions to predict percent cover of six rangeland components. Regression equations were applied to TM imagery to create cover maps for live shrub, dead and live shrub, sagebrush, forb/grass, forb, and bare

ground/rock. Accuracy was assessed at two levels and ranged from 55 to 90%.

The third chapter presents results of sage grouse surveys used with satellite data and GIS to assess habitat use patterns. Habitats used by grouse were compared to availability in the landscape for continuous images of rangeland cover variables, for discrete images of rangeland classes, and for habitat diversity values. Overall, results were comparable to those in studies using traditional methods.

(81 pages)

CHAPTER I

APPLICATIONS OF REMOTE SENSING AND GIS IN WILDLIFE HABITAT MODELING

INTRODUCTION

Managing vegetation distribution and condition is a central focus of the wildlife management profession. Whether the objective is to restore degraded habitat, maintain existing condition, or prevent habitat deterioration, wildlife managers must be able to assess the quantity and quality of habitat and to anticipate change through time. Knowledge of existing and potential habitat condition is fundamental to such wildlife management activities as regulating harvests, maintaining viable populations, and restoring endangered and threatened species.

Although vitally important, habitat inventory and evaluation are among the most costly and time-consuming components of wildlife management programs. Not surprisingly, wildlife scientists and managers have adopted new methods and technologies to increase the efficiency and accuracy of their habitat inventories and assessments. Two such developments addressed in this chapter are remote-sensing technology, and geographical information systems (GIS).

REMOTE SENSING FOR HABITAT CLASSIFICATION AND MAPPING

Remote-sensing technology has been used extensively in such fields as forestry and agriculture to inventory stocks and conditions of resources. Synoptic and repetitive coverage (Carneggie et al. 1983) and decreased bias of interpretation (Mayer 1986) make this technology an attractive alternative to traditional methodology. Satellite imagery may be well suited to wildlife-habitat modeling even when classified for other purposes such as forest-stand inventory or range condition (Mayer 1986).

Spanning a wide range of species, several studies have used remotely sensed data to map habitat and to examine relationships of animals to vegetation class. Habitat types used by grey kangaroos (*Macropus giganteus*), determined from aerial census, were classified and mapped using Landsat Multispectral Scanner (MSS) data (Hill and Kelly 1987). Similarly, Cannon et al. (1982) used satellite imagery to classify vegetative cover types important to lesser prairie chickens (*Tympanuchus pallidicinctus*). Results relating density of displaying males to Landsat-generated resource classes closely paralleled results obtained from conventional field sampling techniques.

Moose (*Alces alces*) habitat classes for a 13 million ha site in eastern Alaska were developed by analyzing

satellite imagery (La Perriere et al. 1980). More recently, Miller and Conroy (1990) used SPOT (Systeme Pour l'Observation de la Terre) imagery to generate maps of winter habitat needed by the endangered Kirtland's warbler (Dendroica kirtlandii).

Such applications may be enhanced by incorporating ancillary data into the digital data base to aid in delineating potential habitat classes. For example, physiographic masks and digital terrain data are frequently used to improve classification accuracy. Habitat classes appearing spectrally similar often can be differentiated by their occurrence in different physiographic units or elevations (Shasby and Carneggie 1986).

A study in Arizona used digital terrain data consisting of slope, aspect, and elevational information to identify potential bighorn sheep management areas on an Arizona study site. All pixels representing land between 900 and 2500 m on slopes greater than 20% in areas designated as Mohave Desert, Great Basin Desert, and mountain-shrub types were considered potential habitat (Bonner et al. 1982).

Talbot and Markon (1986) used Digital Elevation Model (DEM) data, produced by digitizing elevation contours from USGS topographic maps, to classify habitat types on Nowitna National Wildlife Refuge, Alaska. Slope and aspect data derived from DEM were effective in distinguishing mountain shadows from water. Elevational data were used to separate

lowland scrub classes from subalpine scrub, and elevational and aspect data were used to label spectral classes on northerly aspects positioned in shadow at the time of fly-over.

Production of dabbling ducks in the prairie pothole region of North America is related to the total area of wetland habitat present between May and July (Smith et al. 1964). Gilmer et al. (1980), working in this region, analyzed MSS data as a means of determining the amount of wetland habitat present within a 38,876 km^2 study area. Open water was identified on the basis of distinctive reflectance in MSS band 7. A NASA aircraft collected medium-scale (1:20,000) imagery in a portion of the study area on a date close to that of the Landsat flights. The aircraft samples provided a correction factor for adjusting the total wetland estimates derived from Landsat data. Regression analysis predicted the total amount of wetland habitat present. This double-sampling approach provided information on wetland types and land uses, thereby increasing the value of the Landsat assessments of waterfowl habitat.

Landsat winter scenes have helped solve the difficult problem of separating coniferous-forest classes from wetlands on summer imagery of Alaskan wildlife refuges (Shasby and Carneggie 1986). Wetland communities, normally frozen and snow-covered in winter, exhibit higher reflectance than taller coniferous-forest communities

(Shasby and Carneggie 1986, Talbot and Markon 1986). A density slice performed on the winter data was used to generate a mask of all areas with a brightness value greater than that associated with areas of forest or scrub. This mask was applied to classified summer data to stratify and correct misclassified communities (Talbot and Markon 1986, 1988).

USING GEOGRAPHICAL INFORMATION SYSTEMS IN HABITAT EVALUATIONS

Manual mapping and overlay procedures are fast being replaced in wildlife habitat work by geographical information systems (GIS). GIS may be used to efficiently store, retrieve, manipulate, analyze, and display spatial data as specified by the user. The utility of remotely sensed data is compounded through integration with other spatial information in the GIS environment (Jensen 1986).

Hodgson et al. (1987) used a GIS proximity-analysis procedure to determine wood stork (*Mycteria americana*) foraging habitat within 10 km of a rookery. Land-cover types associated with foraging locations were identified by Thematic Mapper (TM) imagery analysis, and the land-cover map was input into a GIS. Proximity procedures determined the total foraging area in 1 km zones surrounding the nesting colony.

In the Flathead National Forest, Montana, data layers concerned with elevation, aspect, proximity to water,

vegetation type, and area of vegetation were combined in a GIS to locate and rate elk calving habitat. The data plane depicting calving areas was used in conjunction with one depicting distance to roads to evaluate the need for road closure in areas of critical habitat (Hart et al. 1985).

A study of spotted owl (Strix occidentalis) habitat preference in Washington began with a land-cover map produced from satellite imagery. Owl locations determined by radio telemetry were digitally overlaid onto land-cover data to reveal habitat preference and home range composition by land-cover class. Old-growth forest was found to be used more in proportion to its availability than other cover types (Young et al. 1987).

PREDICTIVE MODELING WITH SATELLITE IMAGERY AND GIS

A primary objective of wildlife-habitat relationship models is to predict wildlife occurrence or abundance from some set of habitat-condition attributes. Simple species-occurrence models assume that a species is likely to be present in an area if habitat conditions are adequate to fulfill its life needs (Salwasser 1986). More complex models use habitat quality in evaluating the capacity of habitat to support populations at various levels.

A study on Sauvie Island, Oregon, evaluated the capability of habitat types to support kestrel (Falco sparverius) nests and used this information to predict

population levels (Lyon 1983). Landsat imagery was classified and used to develop a map of vegetation communities. Next, the researcher measured area, interspersion, and juxtaposition of vegetation within the habitat mosaic. A census of kestrels on the island revealed that several factors seemed to influence the location of nest areas. These included presence and relative abundance of land-cover types which supply food and cover, interspersion (spatial distribution) of cover types within the area of daily activity, and accessibility or juxtaposition of cover types. These factors were used to develop the model variables and to weight the relative contribution of each variable. The model was evaluated by searching for kestrel nests within ten 100-pixel areas having high model ratings. Seven of the ten areas were verified as kestrel nesting areas. Total numbers of kestrels were found to increase with the model's ratings of habitat condition.

Palmeirim (1988) predicted passerine bird densities in a Kansas study area by using TM data in association with a GIS. Bird locations derived from field observations were overlaid onto a map of vegetative cover types to identify patterns of habitat-type preference. Spatial factors, such as preference or avoidance of edges and size of habitat patch, were taken into account in developing a probability map of species occurrence. The probability map, combined with field census information, produced additional maps

depicting species densities within the study area.

Palmeirim (1985) also used this approach to evaluate potential reintroduction sites for ruffed grouse (Bonasa umbellus). Wooded areas were isolated from a vegetative cover map, and all forest patches farther than 300 m from other forested areas and smaller than 4 ha (smallest possible home-range size) were eliminated from consideration. As grouse in the Kansas study region are known to depend on the dense understory vegetation of younger forests, and such understories only occur in forest edge, areas on the map were ranked in suitability according to forest age and distance from edge. Potential grouse release sites were selected on the basis of habitat suitability and proximity to roads providing access.

CONCLUSIONS

The majority of wildlife habitat is not managed specifically for wildlife. Therefore, integration of wildlife habitat concerns into multi-resource planning is vitally important if wildlife objectives are to be achieved. Such integration requires practical wildlife habitat models that predict potential changes in species occurrence or abundance following changes in habitat quantity, quality, and distribution (Mayer 1986, Salwasser 1986).

Satellite remote sensing and GIS offer significant potential for habitat modeling and evaluation, particularly

at the landscape level. However, the zeal with which wildlife managers and others have embraced these new technologies has led to inflated expectations of their capabilities.

Satellite imagery is often compared to aerial photography. Image analysis is frequently suggested as an alternative to photointerpretation without assessing the individual needs of resource managers. Depending on specific project requirements for high spectral or spatial resolution, flexibility of data acquisition scheduling, and synoptic viewing of broad landscapes, either satellite imagery or aerial photography may be required.

While habitat modeling capabilities have been expanded and many mundane map-making tasks are shortened by invoking GIS, many resource managers have underestimated the time, costs, training, and data acquisition needs associated with initiating an automated mapping system. Managers often think in finite terms of which layers are planned for their GIS. Later they realize that due to new ideas and management needs, new data layers may always be needed and that updating and editing of GIS data files may be a never-ending process.

Despite these admonitions, satellite remote sensing and GIS offer the capability to analyze wildlife habitat in ways never before possible. While the most common use today is habitat classification, prediction of species occurrence or abundance is an another practical

application. By combining GIS technology with satellite or other digital imagery, options for classifying, characterizing, and displaying wildlife habitats and for testing hypotheses on the relationships of species to environment are expanded. The potential applications in natural resources management are currently limited only by human imagination, cost, and the available computer technology.

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CHAPTER II

USING LANDSAT THEMATIC MAPPER TO DEVELOP CONTINUOUS IMAGES OF RANGELAND COVER

INTRODUCTION

Two distinctly different approaches to vegetation characterization exist within the ecological literature. The first divides vegetation into units which can be combined to form classes or types. The second recognizes that vegetation occurs as a continuum in space and time and is only differentiated into units through arbitrary means (McIntosh, 1967). There are proponents of each concept (McIntosh, 1967; Grieg-Smith, 1980). However, within satellite-remote-sensing literature, vegetation is generally viewed as occurring in a well defined mosaic formed from discrete units, and satellite data have tended to be classified accordingly (Wood and Foody, 1989). Image-classification error may be partly attributable to the assignment of class boundaries to an image where, in fact, a gradient of change exists (Allum and Dreisinger, 1987).

Scale may be important in deciding whether to treat vegetative data as classes or as a continuum. At a coarse scale, as represented by plant communities, discrete units may be satisfactory, while gradients may be more appropriate for characterizing vegetation at finer scales (McIntosh, 1967).

Traditional methods for modeling vegetation components from remotely sensed data involve two approaches. The first, canopy modeling (Strahler et al., 1986), uses radiative-transfer theory, energy-budget relationships, and vegetation architecture to predict scene elements through model inversion. Franklin and Strahler (1988) demonstrated this model type in their predictions of tree size, density and cover. Pech and Davis (1987) used a similar approach to estimate fractional cover of trees, bare soil, and litter from Landsat Multispectral Scanner (MSS) data by taking into account sunlit portions of vegetative components and shadow. Li and Strahler (1985) developed a canopy model that employs tree geometry and angle of illumination. When inverted, the model yields estimates of tree height and spacing from Landsat data.

Other model types are based solely on relationships between band reflectances and measurements of landscape components. Typically, these use regression to relate reflectances from one or more wavebands to field or photo-interpreted measurements of vegetation (Strahler et al, 1980). This methodology has been used to predict biomass (Briggs and Nellis, 1989; Franklin, 1986), basal area of forest stands (Franklin, 1986), and vegetation cover (Vujakovic, 1987; Butera, 1986; Graetz et al., 1988; Pech and Davis, 1987).

This paper presents an approach for characterizing the

cover components of a rangeland community from remotely sensed data. Thematic Mapper (TM) band combinations are used in a multiple linear regression to produce continuous images of percent coverage for various landscape elements.

STUDY AREAS

I selected three study areas totaling 55,414 ha in Rich and Morgan Counties, Utah, and Lincoln and Uinta Counties, Wyoming (Figure 1). The region is characterized by rolling terrain intersected by a series of drainages. Slopes range from 0% to 70%. All areas are located between 1889 m and 2437 m elevation, primarily within sagebrush steppe.

Shrub species include sagebrush (Artemisia spp.), rabbitbrush (Chrysothamnus spp.), greasewood (Sarcobatus vermiculatus), shadscale (Atriplex confertifolia), gray horsebrush (Tetradymia canescens), western snowberry (Symphoricarpos oreophilus), serviceberry (Amelanchier spp.), and bitterbrush (Purshia tridentata). Small scattered stands of juniper (Juniperus osteosperma) and aspen (Populus tremuloides) are present. Coniferous forest (predominantly Douglas fir, Pseudotsuga menziesii, and subalpine fir, Abies lasiocarpa) occurs in small stands at higher elevations.

Herbaceous vegetation occurs as a varied mixture of grasses and forbs. Crested wheatgrass (Agropyron cristatum) is the dominant grass on dry sites, while

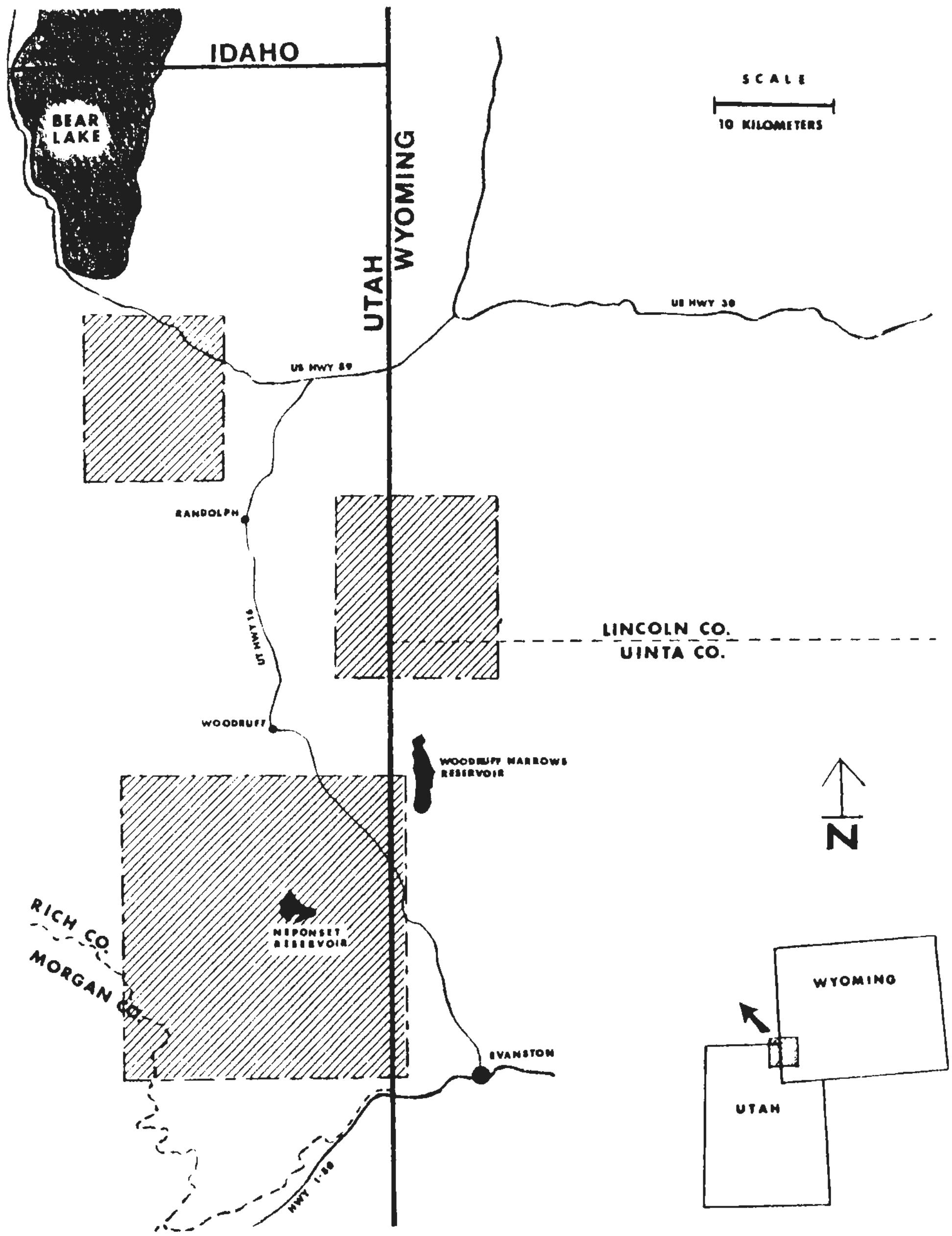


Figure 1. Study area location

various sedges and rushes (Carex spp. and Juncus spp.) dominate wet meadow sites. Common forbs include locoweed (Astragalus spp.), beard tongue (Pentstemon spp.), fleabane (Erigeron spp.), bluebells (Mertensia spp.), and giant hyssop (Agastache urticifolia). Cultivated meadows, predominantly alfalfa (Medicago spp.), are interspersed with the uncultivated rangeland types.

METHODS

Preliminary Data Processing

A July 1, 1986, Landsat-5 Thematic Mapper scene covering the study areas was digitally analyzed using the Earth Resources Data Analysis System (ERDAS) software package. I extracted satellite data for the three study areas from computer-compatible tapes (CCT). Six bands of satellite data covering the reflective portion of the visible and infrared areas of the electromagnetic spectrum (TM Bands 1-5 and 7) were selected. Although the study areas were geographically separated, I spliced together images of all three for digital analysis. I then used the histogram minimum method (HMM) (Chavez, 1975) to adjust for atmospherically induced scattering of electromagnetic radiation.

I produced a field sampling guide to identify and sample spectrally homogeneous data-collection sites representing the entire spectral range. First I applied

the Tasseled Cap Transformation (Crist and Cicone, 1984) to the 6-channel TM data to better separate vegetation types and to reduce dimensionality. Then I classified the image to 75 spectral classes using an unsupervised minimum-distance-to-means classification scheme. The 75-class image was grouped into 16 preliminary cover classes (15 terrestrial classes and 1 aquatic) representative of all three sites. I accomplished this through examination of signature plots and scatter diagrams and from personal knowledge of the study area. I then subset the classified image into individual files for each of the three sites and georeferenced each one by using the nearest-neighbor resampling method. I then printed a 1:24,000-scale map from the 16-class image for use in vegetation sampling.

Field Sampling

I selected vegetation cover plots from homogeneous groupings of 9 or more pixels of each of the 15 land classes. Each of the 15 classes was replicated 18 times in a stratified random sampling scheme. I sampled study sites in proportion to the area they contributed to the overall study area. Each pixel group (ground truth plot) was required to be within 420 m of an easily identifiable feature to assure accurate location from map to ground.

I used a point-sighting method (Floyd and Anderson, 1982) to gather ground-cover information. In each of 254 rangeland plots, I recorded 900 points as live shrub,

dead/live shrub, sagebrush, forb/grass, forb, or bare ground/rock. Plots containing aspen or coniferous forest were noted, but not sampled. By using aerial photos and U.S.G.S orthophotoquads, I verified 34 plots as being water.

Development of Continuous Images of Cover Components

I used nearest-neighbor resampling to georeference the unprocessed 6-band image. I masked forest and water types from the image by overlaying the 75 spectral clusters. Pixels corresponding to clusters identified as forest or water were removed from the data set. I considered the remaining area (53,888 ha) to be rangeland, of types varying from natural and cultivated meadows to shrublands.

I digitized the locations of ground-cover plots and overlaid them on the unprocessed image as 3 x 3 pixel groups. Center pixels of each group matched the location of field sites. I averaged brightness values (BV) from each of the ground-truth pixel groups, by waveband.

Inspection of average waveband-brightness values and cover data at ground-truth plot locations revealed non-normally distributed cover data and nonlinear relationships between cover data and brightness values. I applied an arcsin square root transformation to each of the percent canopy-cover variables to normalize the data sets. I also used transformations including log BV, 1/BV, BV^2, and $BV^{1/2}$ to linearize relationships of brightness values and cover

data.

I used a stepwise multiple linear model to regress brightness values and transformed brightness values against arcsin (% canopy cover)$^{1/2}$ of each rangeland-cover variable. By applying the resulting equations, pixel by pixel, to the unclassified rectified image and taking the sine of the resulting digital values and squaring them, I created single-band images representing canopy cover of each component.

Inspection of the continuous images for live shrub, dead/live shrub, and sagebrush revealed areas of wet meadow predicted to be high-density brush when, in fact, no brush existed in these areas. Standing water within herbaceous vegetation apparently caused the discrepancy by reflecting darkly, as high-density brush might have. I removed these "pseudo-shrub" components from the meadow areas by means of a FORTRAN program. The program used conditional statements to eliminate dense brush cover from areas where brush would not occur (i.e., areas characterized by dense forb/grass cover and little visible bare ground).

Using a 10-fold cross-validation procedure (Verbyla, 1986) I compared regression-predicted cover values for each cover component against actual cover values obtained from field verification plots. Accuracy was assessed at two levels. Predicted values were considered to be accurate if they fell within $\pm$ 10% or $\pm$ 15% of the range of values observed in field plots (Table 1).

Table 1. Observed and regression-predicted ranges of percent cover of rangeland components within the study area. Column labeled "Percent Outside" indicates percentages of pixels in the predicted range which are outside the range of the observed. _n_ = 598,755.

Rangeland Component	Observed Range (% cover)	Predicted Range (% cover)	Percent Outside
Live Shrub	0 - 72	0 - 100	0.0149
Dead/Live Shrub	0 - 74	0 - 100	0.0129
Forb/Grass	1 - 92	0 - 100	0.7674
Forb	0 - 39	0 - 100	0.0070
Sagebrush	0 - 56	0 - 100	0.3248
Bare Ground/ Rock	0 - 83	0 - 99	0.0683

RESULTS AND DISCUSSION

Regression Equations

Each of six equations predicting cover components from combinations of TM band transformations was found to be a significant predictor of percent canopy cover of the respective components ($p < .0000$) and accounted for 35% to 82% of the variance (Table 2). Examples of the images produced are displayed in Figure 2.

Results were as expected from reflectance patterns attributable to leaf physiology, chlorophyll absorption, internal leaf structure, and leaf moisture (Campbell, 1987). The equation predicting percent cover of forb/grass consisted largely of transformed brightness values of the infrared- and green-reflecting TM bands (bands 4,5,7 and 2). The percent forb-cover equation was similar in that

Table 2 (a-f). Results of multiple linear regression analysis of arcsin (% cover)$^{1/2}$ of individual rangeland components, as a function of TM waveband brightness values.

a. Live Shrub

Independent[a] Variables	Regression Coefficient	Partial r^2	p
1/Band 1	16.4750	0.0341	0.00365
1/Band 2	-9.4655	0.0185	0.03281
1/Band 4	-104.0730	0.0128	0.07629
1/Band 7	-44.5119	0.1468	0.00000
Log Band 3	-1.6500	0.0699	0.00003
Log Band 4	-5.0915	0.0408	0.00144
Log Band 5	-1.6781	0.0452	0.00079
Band 1^2	-8.9987×10^{-5}	0.0202	0.02586
Band 2^2	4.6594×10^{-4}	0.0447	0.00085
Constant	18.2038		
SE	0.1613		
Adj. r^2	0.6199		
r^2	0.6334		
Multiple r	0.7959		
F ratio (9,244 df)	46.841		
p	< 0.0000		

[a]Bands 1-7 refer to the brightness values from TM bands.

Table 2, continued.

b. Dead/Live Shrub

Independent Variables	Regression Coefficient	Partial $\underline{r}^2$	$\underline{p}$
1/Band 1	16.0080	0.0318	0.00503
1/Band 2	-9.5536	0.0186	0.03250
1/Band 4	-103.8149	0.0126	0.07923
1/Band 7	-44.9816	0.1476	0.00000
Log Band 3	-1.6855	0.0717	0.00002
Log Band 4	-5.1351	0.0409	0.00143
Log Band 5	-1.7451	0.0480	0.00054
Band 1^2	-8.7919×10^{-5}	0.0190	0.03065
Band 2^2	4.6247×10^{-4}	0.0434	0.00101
Constant	18.5167		
SE	0.1625		
Adj. $\underline{r}^2$	0.6267		
$\underline{r}^2$	0.6399		
Multiple $\underline{r}$	0.8000		
$\underline{F}$ ratio (9,244 df)	48.184		
$\underline{p}$	< .0000		

c. Sagebrush

Independent Variables	Regression Coefficient	Partial $\underline{r}^2$	$\underline{p}$
Band 2^2	1.75669×10^{-4}	0.0308	0.00555
Band 1	-0.0056	0.0130	0.07274
Band 4	0.0071	0.0207	0.02360
1/Band 3	12.3461	0.0507	0.00035
1/Band 4	136.5348	0.1034	0.00000
1/Band 7	-28.2568	0.0689	0.00003
Band $5^{1/2}$	-0.0720	0.0235	0.01563
Constant	-0.8807		
SE	0.1482		
Adj. $\underline{r}^2$	0.6076		
$\underline{r}^2$	0.6185		
Multiple $\underline{r}$	0.7864		
$\underline{F}$ ratio (7,246 df)	56.9690		
$\underline{p}$	6.0000 x 10-14		

Table 2, continued.

d. Forb/Grass

Independent Variables	Regression Coefficient	Partial $\underline{r}^2$	$\underline{p}$
Band 4	0.0058	0.1714	0.00000
1/Band 1	-9.5604	0.1165	0.00000
1/Band 5	174.0082	0.1725	0.00000
Band $5^{1/2}$	0.3593	0.1391	0.00000
Band $7^{1/2}$	-0.1894	0.1130	0.00000
Band 2^2	-1.1269×10^{-4}	0.1500	0.00000
Constant	-3.6616		
SE	0.1117		
Adj. $\underline{r}^2$	0.7227		
$\underline{r}^2$	0.7293		
Multiple $\underline{r}$	0.8540		
$\underline{F}$ ratio (6,247 df)	110.9190		
$\underline{p}$	< 0.0000		

e. Forb

Independent Variables	Regression Coefficient	Partial $\underline{r}^2$	$\underline{p}$
Band 7	-0.0452	0.0746	0.00001
1/Band 1	6.3490	0.0214	0.02132
1/Band 3	-10.0696	0.0259	0.01110
1/Band 4	-53.2519	0.0566	0.00016
Log Band 7	2.6315	0.0500	0.00039
Band 4^2	-2.0327×10^{-5}	0.0209	0.02287
Band 7^2	1.6297×10^{-4}	0.0578	0.00013
Constant	-1.3919		
SE	0.1145		
Adj. $\underline{r}^2$	0.3505		
$\underline{r}^2$	0.3685		
Multiple $\underline{r}$	0.6071		
$\underline{F}$ ratio (7,246 df)	20.508		
$\underline{p}$	< 0.0000		

Table 2, continued

f. Bare Ground/Rock

Independent Variables	Regression Coefficient	Partial r^2	p
Band 7	0.0104	0.1831	0.00000
1/Band 1	7.8101	0.1116	0.00000
Band $3^{1/2}$	0.2140	0.3664	0.00000
Band 5^2	-3.0943×10^{-5}	0.2323	0.00000
Constant	-1.3615		
SE	0.1121		
Adjusted r^2	0.8199		
r^2	0.8228		
Multiple r	0.9071		
F ratio (4,249 df)	288.9840		
p	< 0.0000		

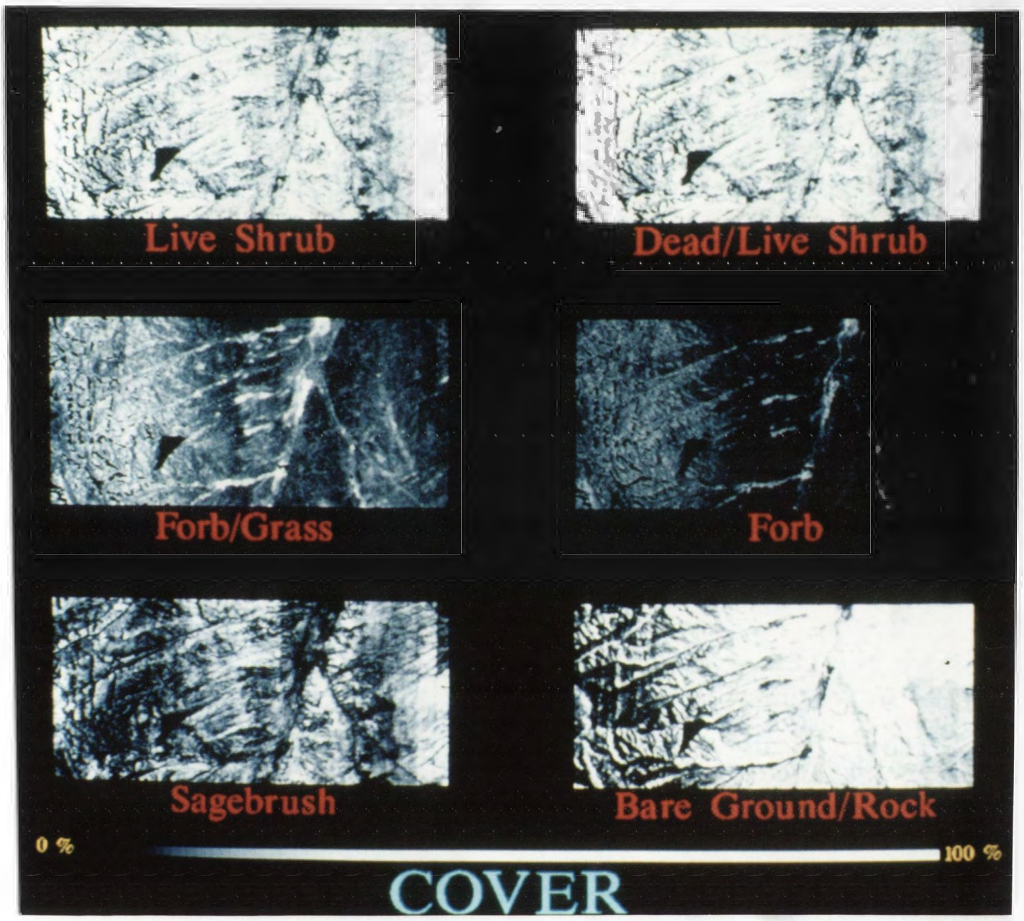


Figure 2. Continuous images of percent cover of 6 rangeland components, as predicted from TM brightness values.

bands 4 and 7 were the primary contributors to the equation.

Examining relationships of waveband brightness to percent cover of live shrub and dead/live required different transformations for each of the 6 bands. Band 7 transformed by 1/BV was the single best predictor. Sagebrush cover also was predicted by an equation using all bands with transformations of bands 3, 4, and 7 contributing the most to the overall equation. Inclusion of band 3 in the equation may result from the overall low greenness of sagebrush and resulting dominance of the soil background.

Transformations of bands 3 and 5 were most useful in predicting coverage of bare ground/rock. Dominance of the red band is not surprising since red-hued soils prevail within the study area. The relatively high partial r^2 value for band 5 (transformed by BV^2) is likely a result of soils reflecting highly in the infra-red regions. However, the weakly negative regression coefficient might indicate the influence of vegetation coverage. Percent cover of bare ground/rock decreases as band 5 brightness values increase. This effect may result from increased vegetation and litter cover reflecting relatively high in the mid-infrared region (Wooley, 1971; Sinclair et al., 1973).

Accuracy Assessment

Overall the percent cover of forb/grass and bare

ground/rock types were the most accurately predicted (Table 3), likely because their spectral signatures are highly distinctive. In contrast, percent cover of the shrub types and forb types exhibit much lower accuracy levels. Decreased accuracy for live-shrub and dead/live-shrub categories may have resulted from the procedure for combining species. Reflectances of high-chlorophyll "green" shrubs (serviceberry, snowberry, rabbitbrush, bitterbrush, and juniper) were combined with those of low-chlorophyll "gray" shrubs (sagebrush, shadscale, greasewood, and horsebrush) to develop the regression equations predicting overall shrub-coverage levels.

Conversely, the band combinations used to predict percent coverage of sagebrush and forb could have predicted coverages of similarly reflecting plant species

Table 3. Results of a 10-fold cross-validation procedure to assess accuracy of regression-predicted cover images. Images were considered accurate if predicted cover values fell within ± 10% or ± 15% of the range of the observed cover values.

Rangeland Component	Accuracy (± 10% of observed range)		Accuracy (± 15% of observed range)	
	(%)	SD	(%)	SD
Live Shrub	54.7564	9.1787	72.7269	10.8275
Dead/Live Shrub	55.1731	8.9856	71.9577	10.4803
Sagebrush	57.9949	9.4337	74.3756	8.0496
Forb/Grass	80.2692	8.0740	91.5103	7.4460
Forb	59.1795	7.0580	74.7295	7.2317
Sagebrush	57.9949	9.4337	74.3756	8.0496
Bare Ground/ Rock	73.0603	13.4774	87.5231	6.8254

inadvertently. The equation predicting sagebrush coverage would likely predict similar coverages of greasewood, shadscale, and other non-green shrubs. Likewise the equation for forb could have predicted percent coverage by grass or deciduous shrub.

Accuracy of all vegetation cover-categories may have been reduced because background reflectance was not considered in the predictive models. In semi-arid environments the amount of vegetation cover is small compared with other landscape features such as litter, lichens, and bare ground (Graetz et al., 1988). Reflectance characteristics of arid and semi-arid environments have been studied by Otterman (1981), Otterman and Tucker (1985), Graetz and Gentle (1982), and Pech et al. (1986). The consensus is that soils are a major landscape component reflecting brightly in all wavebands. Vegetation tends to reduce soil reflectance in proportion to its coverage.

Extensive variations in soil darkness or lightness across the study area may account for much of the predictive error in my study. Vujakovic (1987), working in an area of homogeneous soil color, was able to predict percent cover of green woody vegetation with accuracies above 80%. Elvidge and Lyon (1985) noted that variations in soil and rock brightness affected all ratio- based vegetation indices by inducing overestimates of vegetation on dark backgrounds relative to bright backgrounds. Ustin

et al. (1986) noted that vegetation typically was overestimated on dark soils. In studying a cotton canopy over four different soil types, Huete et al. (1985) concluded that both soil brightness and soil spectral effects influenced greenness measures at low vegetation densities as well as at canopy covers approaching 75%. This conclusion was supported by Williamson's (1989) finding that reflectances from plant species are affected by the soil background even when vegetation covers the field of view of the sensor.

Landscape factors other than soil color may have affected results. For example, senescent vegetation and litter may have darkened reflectances (Pech and Davis, 1987) or raised reflectance in the blue and red bands (TM bands 1 and 3) (Sanger, 1971).

The Form of the Model

Under conditions of homogeneous soil coloration, predominately live vegetation, vertical look angle and constant solar angle, the type of relationship expected between multispectral reflectance and total vegetation cover depends upon the proportion of soil covered by vegetation (Curran, 1980). While the relationship is curvilinear over the range from 0 to 100% coverage (Tucker, 1977), it approaches linearity over the range from 0 to 95% cover (Curran, 1980).

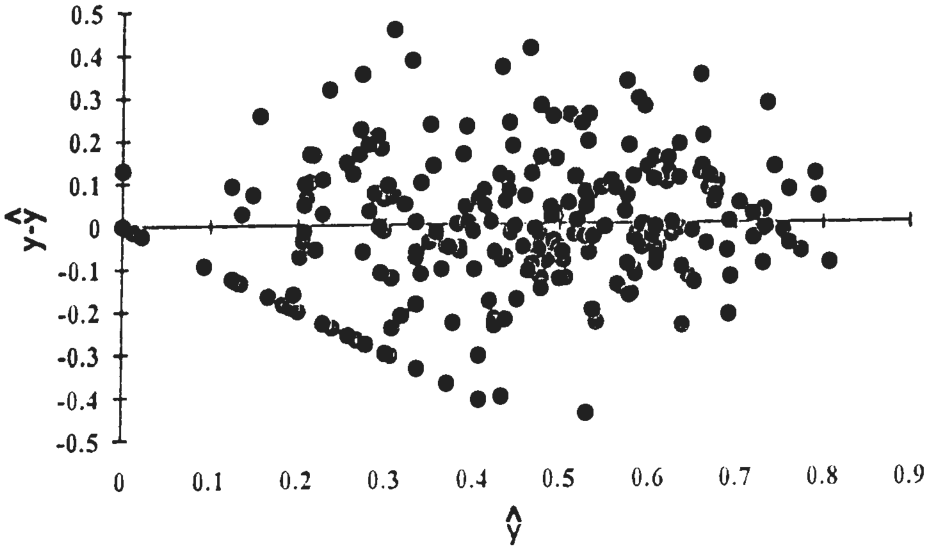
I had assumed that under ideal conditions individual

vegetative components would exhibit a relationship similar to that of total vegetation cover. However, when I plotted coverage by individual components against brightness values of individual wavebands, I observed a curvilinear relationship. Transformations applied to the brightness values in attempts to linearize the relationships produced mixed results. This result may reflect real-world conditions including soil-color variation, non-vigorous vegetation, and shadow. All of these conditions, although likely altering the form of the relationships, were unaccounted for in the model.

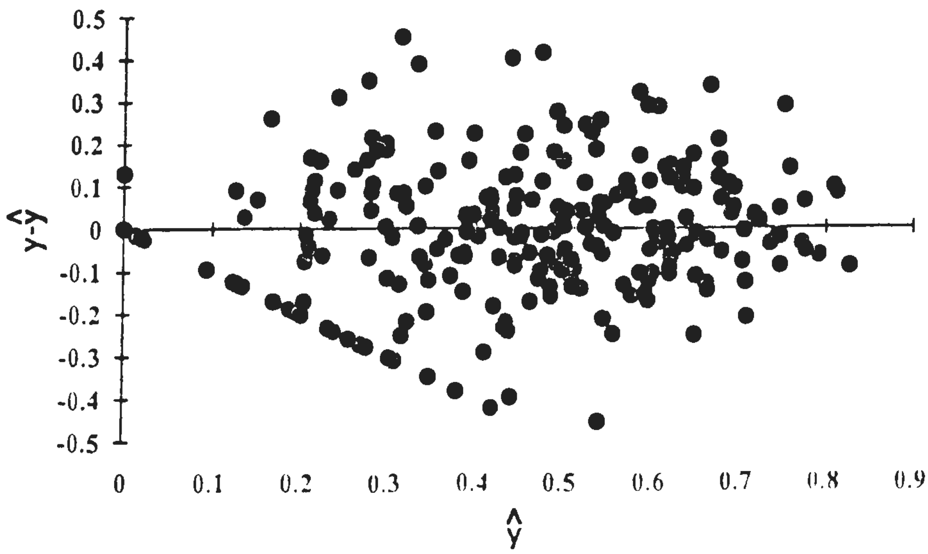
Plots of residuals versus predicted values of percent cover of the landscape components (Figure 3) revealed unequal variances, with residuals distributed equally around zero. Generally, as predicted values increased, their variances increased as well. Lower ranges of cover are predicted more accurately than higher ranges (Table 4), but this may depend on the range limits created in this study. Butera (1986) similarly noted that in estimates of total forest cover, the low-and high-canopy cover ranges were predicted more accurately than were middle ranges. A weighted least squares regression methodology may be useful for equalizing variances (Ott, 1988).

SUMMARY AND CONCLUSIONS

Multiple linear regression was used to produce images predicting percent coverage of rangeland components from TM

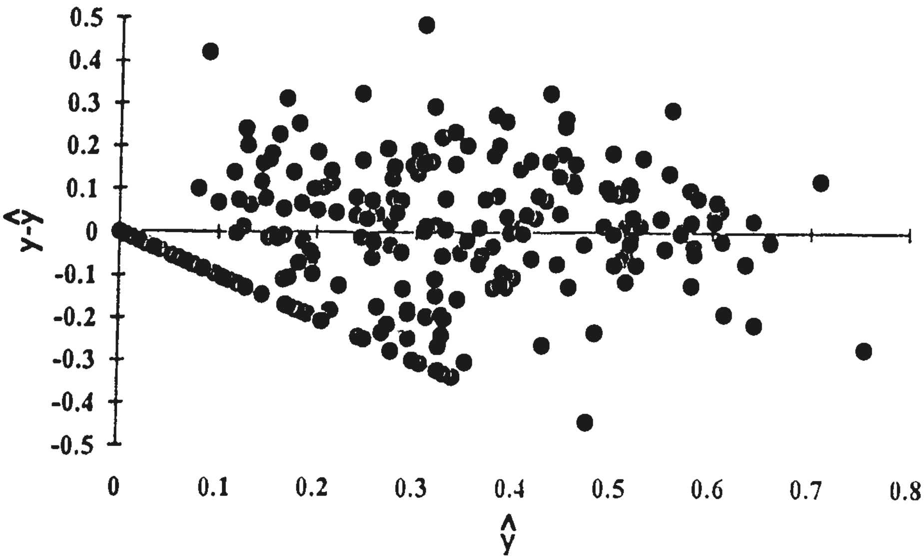


a. Live Shrub

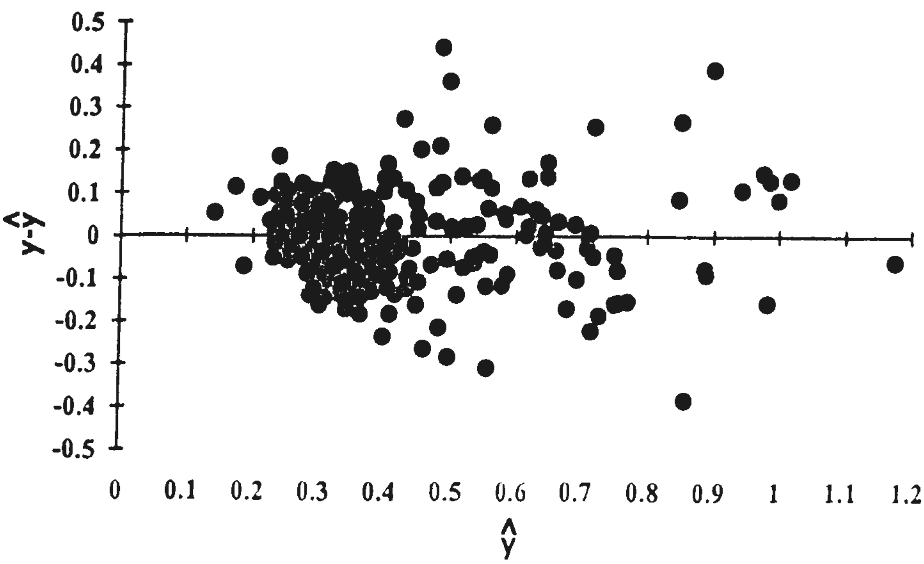


b. Dead/Live Shrub

Figure 3 (a-f). Scatterplots of residuals $(y - \hat{y})$ vs. $\hat{y}$ from regression analysis of arcsin (% cover)$^{1/2}$ of individual rangeland cover components as a function of TM waveband brightness values. Cover components include: a. live shrub, b. dead/live shrub, c. sagebrush, d. forb/grass, e. forb, and f. bare ground/rock. $\underline{n}$ = 254.

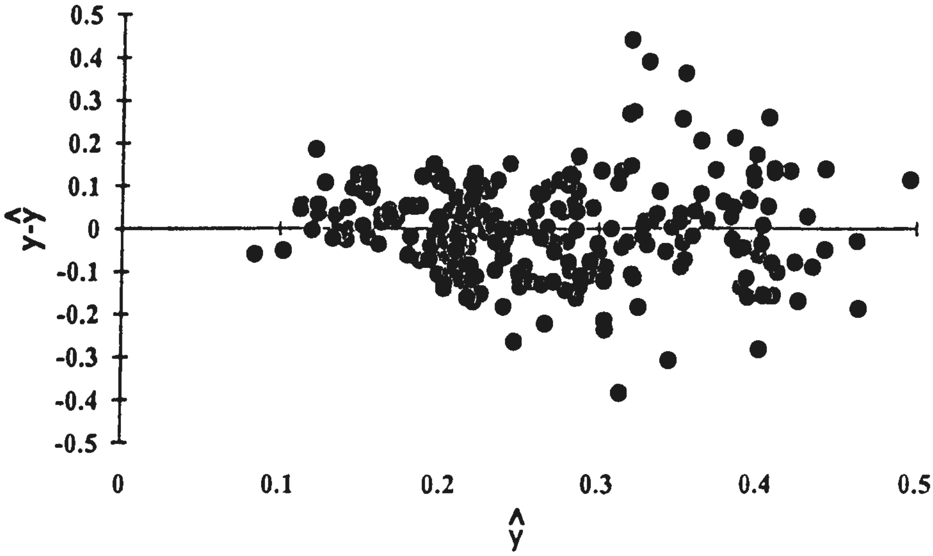


c. Sagebrush

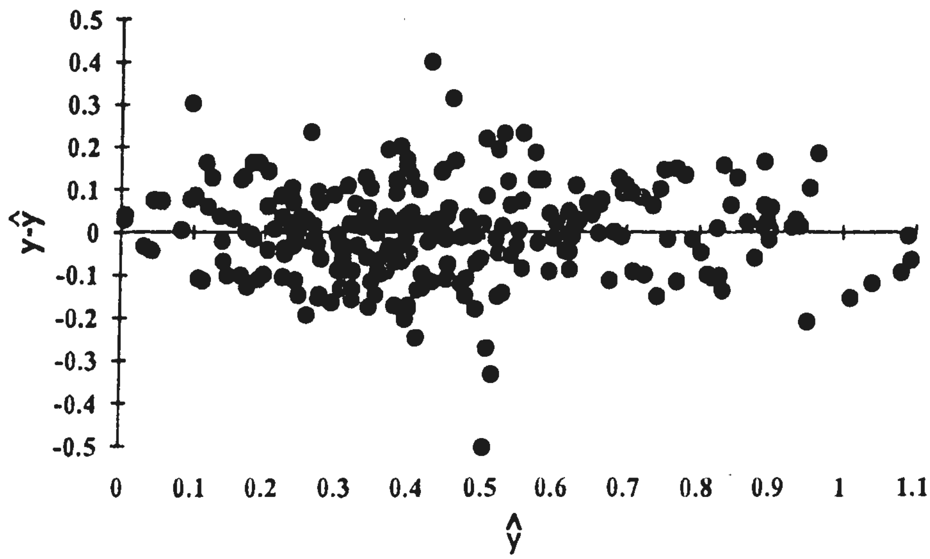


d. Forb/Grass

Figure 3, continued.



e. Forb



f. Bare Ground/Rock

Figure 3, continued.

Table 4 (a-f). Percentages of observed and predicted cover in plots lying within low, medium, and high cover ranges of each element and the percentages of plots accurately predicted (± 10% of the total range of observed values) within each range.

a. Live Shrub

Cover[a] Range	Range Limits (% cover)	Observed ($\underline{n}$ = 254)	Predicted ($\underline{n}$ = 249)	% Accurate
Low	0 - 15	44.49	40.16	67.00
Medium	16 - 27	22.83	30.92	51.95
High	≥ 28	32.68	28.92	41.6
Total		100.00	100.00	

b. Dead/Live Shrub

Cover Range	Range Limits (% cover)	Observed ($\underline{n}$ = 254)	Predicted ($\underline{n}$ = 249)	% Accurate
Low	0 - 16	44.09	41.37	68.93
Medium	17 - 28	23.62	29.32	50.68
High	≥ 29	32.28	29.32	41.10
Total		100.00	100.00	

c. Sagebrush

Cover Range	Range Limits (% cover)	Observed ($\underline{n}$ = 254)	Predicted ($\underline{n}$ = 249)	% Accurate
Low	0 - 6	46.06	41.37	84.47
Medium	7 - 16	19.69	31.73	37.97
High	≥ 17	34.25	26.91	40.30
Total		100.00	100.00	

[a]Ranges represent 33.33% of the total number of pixels within each predicted cover image.

Table 4, continued.

d. Forb/Grass

Cover Range	Range Limits (% cover)	Observed (n = 254)	Predicted (n = 249)	% Accurate
Low	0 - 8	31.89	25.70	98.44
Medium	9 - 12	18.11	22.89	94.74
High	≥ 13	50.00	51.41	65.63
Total		100.00	100.00	

e. Forb

Cover Range	Range Limits (% cover)	Observed (n = 254)	Predicted (n = 249)	% Accurate
Low	0 - 3	31.89	17.67	90.91
Medium	4 - 6	23.23	37.35	68.82
High	≥ 7	44.88	44.98	37.50
Total		100.00	100.00	

f. Bare Ground/Rock

Cover Range	Range Limits (% cover)	Observed (n = 254)	Predicted (n = 249)	% Accurate
Low	0 - 17	53.15	53.01	86.36
Medium	18 - 33	19.29	22.09	58.18
High	≥ 34	27.56	24.90	56.45
Total		100.00	100.00	

brightness values. This procedure enabled me to depict the continuous nature of vegetation within the rangeland community.

Practical applications for the use of continuous-cover imagery may exist in many resource-management fields. For example, the method may be useful in inventories of livestock or wildlife forage over large areas. Wildlife biologists should be able to use this method to evaluate rangeland habitat at various scales from microsite to landscape. With further improvements to increase its predictive accuracy, the methodology presented may offer an attractive alternative to traditional image classification procedures.

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CHAPTER III

USING LANDSAT TO ASSESS SAGE GROUSE SPRING AND SUMMER HABITAT SELECTION

INTRODUCTION

Traditional methods for assessing wildlife habitat are costly in both labor and time. Satellite remote-sensing and geographical-information-system (GIS) technology offer potential to examine habitat over large areas in a more efficient and cost-effective manner. By incorporating remotely sensed interpretations of habitat quality or quantity into a GIS, biologists can model habitat relationships in ways previously not considered possible (Campbell 1987).

The spring and summer habitats used by sage grouse (*Centrocercus urophasianus*) have been evaluated by numerous researchers. These evaluations include Schoenberg and Braun's (1980) study of spring habitat used by adult male and female grouse in Colorado, and Martin's (1970) and Dunn and Braun's (1986) assessments of habitats used by adults and juveniles in Montana and Colorado. Many workers have studied sage grouse nesting and brood-rearing habitat (Klebenow 1969, 1970, 1982; Peterson 1970; Wallestad 1971, 1972; Wallestad and Pyrah 1974; Hulet et al. 1984; Klott and Lindzey 1990). In all cases cited, traditional habitat-evaluation methodology was used. In this paper I present the results of an alternative approach using

satellite imagery and GIS to assess spring and summer habitat selection by sage grouse.

STUDY AREAS

The study area consisted of 3 sites, totaling 55,414 ha, located primarily within Rich County, Utah, but extending into Morgan County, Utah, and Uinta and Lincoln Counties, Wyoming (Chapter 2, Figure 1). Two of the sites are public lands administered by the U.S. Bureau of Land Management. The third is part of Deseret Land and Livestock Company, a privately owned ranch. Vegetation and topographic characteristics of the study area are described in Chapter 2.

METHODS

Image Processing and Development of Cover Maps

Habitat evaluation was based on a July 1, 1986, Landsat-5 Thematic Mapper (TM) scene covering the study area. I extracted 6 bands of digital satellite data from computer-compatible tapes (CCT). TM bands 1, 2, and 3 (0.45-0.52 um, 0.52-0.60 um, and 0.63-0.69 um) were in the visible portion of the electromagnetic spectrum, band 4 (0.76-0.90 um) was in the near-infrared portion, and bands 5 and 7 (1.55-1.75 um and 2.08-2.35 um) were in the mid-infrared range. I did all digital image processing with the Earth Resources Data Analysis System (ERDAS) software

package.

I used a previously classified and georeferenced image of the study area (see Chapter 2) containing 16 preliminary cover classes (15 terrestrial and 1 aquatic class) to produce a 1:24,000 scale print map for sampling vegetation cover. Using a stratified random sampling scheme, I selected ground-truth plots represented by homogeneous grouping of 9 or more pixels. Each pixel group was within 1/4 mile of an easily identifiable feature to ensure accurate location from map to ground.

During the summer of 1989, I used a point-sighting method (Floyd and Anderson 1982) to sample cover characteristics at ground-truth plots. At each of 254 rangeland plots, I recorded 900 points as live shrub, dead/live shrub, sagebrush (Artemisia spp.), forb/grass, forb, and bare ground/rock. Sixteen plots were located in forest while 28 were in the aquatic type. I noted these classes, but did not quantitatively sample them. I used spectral signatures associated with forest and water types to mask out these types, temporarily removing them from the analysis. I considered the remaining 53,888 ha to be potential grouse habitat, ranging from natural and cultivated meadows to shrubland.

A stepwise multiple linear-regression procedure (see Chapter 2) yielded predictions of percent cover for the various rangeland variables from combinations of TM waveband brightness values. By applying regression

equations pixel by pixel to the unprocessed image, I created continuous images representing percent cover of each cover variable (Figure 2, Chapter 2).

I formed discrete habitat classes from combinations of variables representing sage grouse habitat conditions for cover and food. Dead/live shrub was selected to represent cover, as my observations of grouse within the study area showed the use of all shrub types for cover in the summer months. Dominance of forbs in grouse summer diets (Patterson 1952:321; Klebenow 1969, 1970; Peterson 1970; Wallestad 1971; Wallestad et al. 1975) would normally have dictated selection of the forb variable to represent feeding habitat in the discrete image. However, given low accuracy of prediction of percent forb coverage (Chapter 2), I used the forb/grass variable instead as an indicator of available food resources. A FORTRAN program combined the two variables according to criteria specified in Table 5. The forest and water classes previously masked out of the continuous image were digitally overlaid for inclusion in the discrete image of detailed rangeland cover (Figure 4). For comparison purposes I combined all range classes to form another image of generalized land cover classes (rangeland, forest, water) (Figure 5).

I assessed the accuracy of the continuous image with a 10-fold cross validation procedure (Verbyla 1986). I withheld a random sample of 1/10 of the total sample of vegetation measurements and corresponding TM brightness

Table 5. Ranges of percent cover of continuous image variables used in development of the discrete image of rangeland cover classes.

Discrete Classes Detailed Range Image	Continuous Image Variables[a]	
	Dead/Live Shrub % Cover	Forb/Grass % Cover
Sparse Shrub-Sparse Forb/Grass	≤ 17	≤ 8
Sparse Shrub-Medium Forb/Grass	≤ 17	> 8 and ≤ 20
Sparse Shrub-Dense Forb/Grass	≤ 17	> 20
Dense Shrub-Sparse Forb/Grass	> 17	≤ 8
Dense Shrub-Medium Forb/Grass	> 17	> 8 and ≤ 20
Dense Shrub-Dense Forb/Grass	>17	> 20

[a]Range limits were derived from histograms of each continuous-image variable. Approximately one-third of all pixels in the study area had % cover of dead/live shrub ≤17, while two-thirds of pixels had % cover values > 17. For the forb/grass variable, approximately one-third of all pixels were in each of the sparse, medium, and dense categories.

Sparse Shrub-
Sparse Forb/Grass

Dense Shrub-
Sparse Forb/Grass

Sparse Shrub-
Medium Forb/Grass

Dense Shrub-
Medium Forb/Grass

Sparse Shrub-
Dense Forb/Grass

Dense Shrub-
Dense Forb/Grass

Forest

Water

Figure 4. Rangeland cover classes produced from a July 1, 1986, TM scene covering a portion of the study area. Scale = 1:40,000.

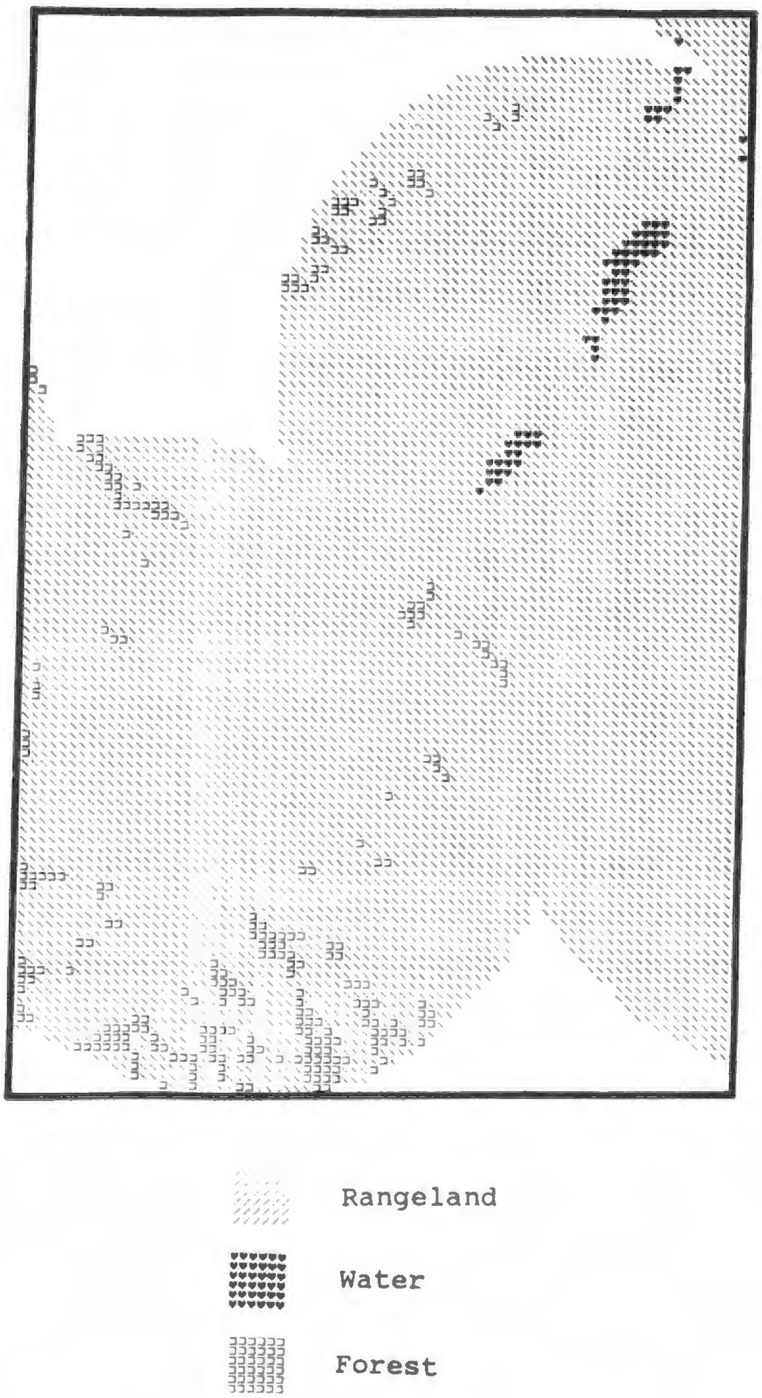
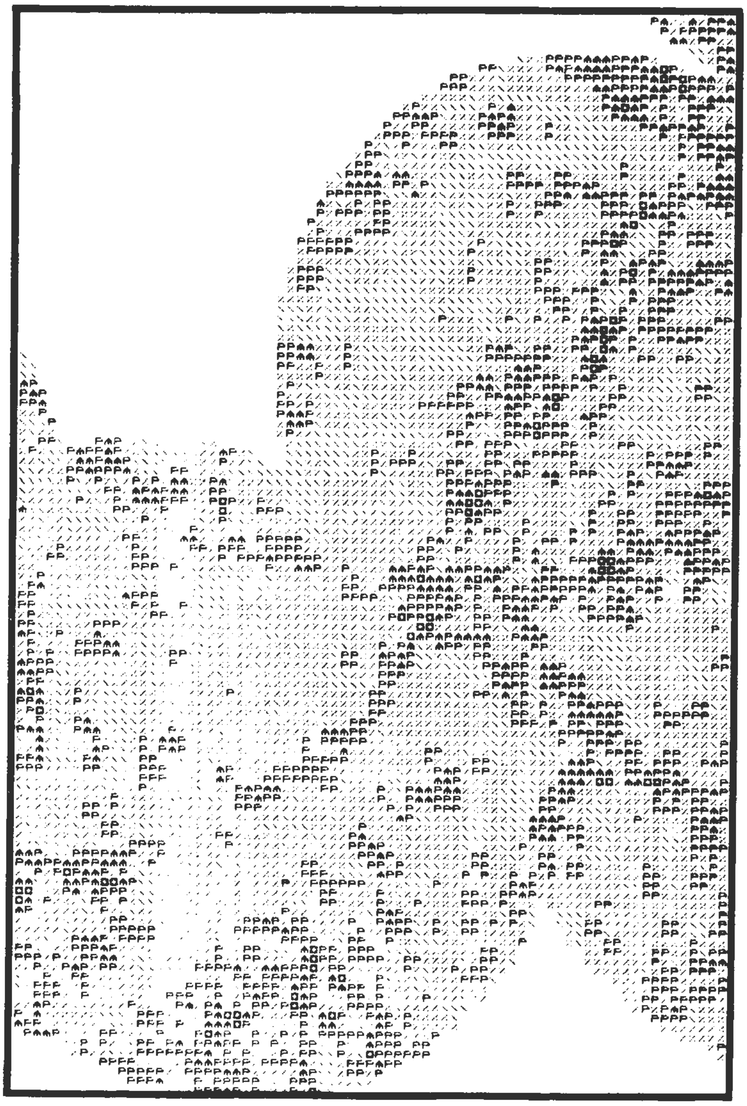


Figure 5. Generalized land-cover classes, as produced from a July 1, 1986, Landsat TM scene covering a portion of the study area. Scale = 1:40,000.

values while regression equations were generated for the remaining values. This process was repeated 10 times. I compared the results with values derived from ground-truth sampling. Two levels of accuracy were considered. The regression-produced image was considered to be accurate if predicted values of percent cover fell within $\pm$ 10% or $\pm$ 15% of the range of observed values for that variable. I averaged the results from the 10 trials.

I assessed accuracy of the discrete image in much the same manner, in that regressions from the 10-fold procedure were used to create 10 separate discrete images. I used a confusion matrix to compare combined classes from each discrete image with actual classes formed from ground-truth data.

Using a GIS, I applied a diversity filter to the discrete image to obtain a measure of habitat diversity. I used a process which calculated the number of classes contained within a 3 x 3 pixel window and entered that value in the center pixel. Since the image contained 8 cover classes, 1 less than the 9 possible within the window, diversity values ranged from 1 (low diversity) to 8 (high diversity). As the filter passed through the discrete image, it produced an image of habitat diversity values associated with each 9 pixel area (Figure 6).



HABITAT DIVERSITY VALUES

Figure 6. Map of habitat diversity generated from a classified TM image of a portion of the study area. Habitat diversity values range from 1 (homogeneous habitat) to 8 (habitats comprised of 8 different habitat types). Scale = 1:40,000.

Digital Overlays of Grouse Locations

A spotlight and long-handled net (Giesen et al. 1982) were used to trap 23 females and 7 male sage grouse on wintering grounds and on leks in 1986 and 1987. Birds were equipped with radio transmitters fitted to ponchos. I recorded nesting locations of hens and weekly feeding and loafing locations of all grouse on 1:24,000 topographic maps. Because survival of radio-equipped birds was poor, I obtained additional grouse locations along transects and while attempting to locate the radio-equipped birds. I sorted grouse observations ($\underline{n}$ = 377) by season (April-June and July-September) and by age/sex category (hens without broods, cocks, broods with or without a hen present, and nests) (Table 6).

Table 6. Number of sage grouse observations (single bird and flocks) occurring in the early and late seasons during 1986 and 1987 in Rich and Morgan Counties, Utah, and Uinta and Lincoln Counties, Wyoming.

Grouse Category	Season	
	Early (April-June)	Late (July-Sept.)
Broods	19	91
Hens	62	114
Cocks	29	45
Nests	17	--
Total	127	250

I digitized grouse locations by category. Because precisely locating grouse was difficult in some types of terrain, and because the birds tended to be in flocks spread over a wide area, I added a 1-pixel buffer to each digitized point to form a grouse location window 3 x 3 pixels in size. I then digitally overlaid the location windows for each season and age/sex category onto the continuous images, the discrete image of detailed range classes, and the diversity image to form mosaics of habitats used by grouse. I used Chi-square analysis and Bonferonni z confidence intervals (Neu et al. 1974, Byers et al. 1984) to assess sage grouse use of habitat. Results were considered significant if $p < 0.05$.

Johnson (1980) indicated that conclusions about animal selection or avoidance of environmental components may be biased by the investigator's arbitrary judgment of what is or is not available to the animal. Choosing an analysis area in excess of that which an animal may travel could show markedly different proportions of each habitat available for use by an animal than would be concluded by selecting a smaller area (Haywood 1988). To avoid this problem, I limited the analysis area to that area which a sage grouse could travel in one day's time. Patterson's (1952:180) maximum travel distance estimate of 1 mile per day was used to digitally create a circle of 1.6 km radius (54 pixels) around each grouse location. Collectively, these circles formed the analysis area for evaluating

habitat preference and avoidance (Figure 7).

RESULTS AND DISCUSSION

Accuracy Assessment of Cover Maps

Results of the accuracy assessment performed on the continuous images of percent cover of individual habitat components are shown in Table 3 of Chapter 2. Bare ground/rock and forb/grass cover were predicted with high accuracy (73-80%). Predicted accuracies were lower for the various shrub categories and the forb component, likely because of confounding effects described in Chapter 2.

Confusion matrices used to assess accuracy of both images of discrete classes (generalized land cover and range cover) are shown in Tables 7 and 8. Generalized land-cover classification was accomplished with 95.7% accuracy, far exceeding the 80% level considered adequate for land-use mapping (Anderson et al. 1976). The finer detail of the range type map lowered overall accuracy levels to 60.5% with individual range-class accuracies varying widely. The discrete image was subject to the same error-producing factors that affected the continuous images from which it was produced. In addition, the detailed discrete image is flawed by error caused by artificial imposition of class bounds on an otherwise continuous data set (Allum and Dreisinger 1987, Wood and Foody 1989).

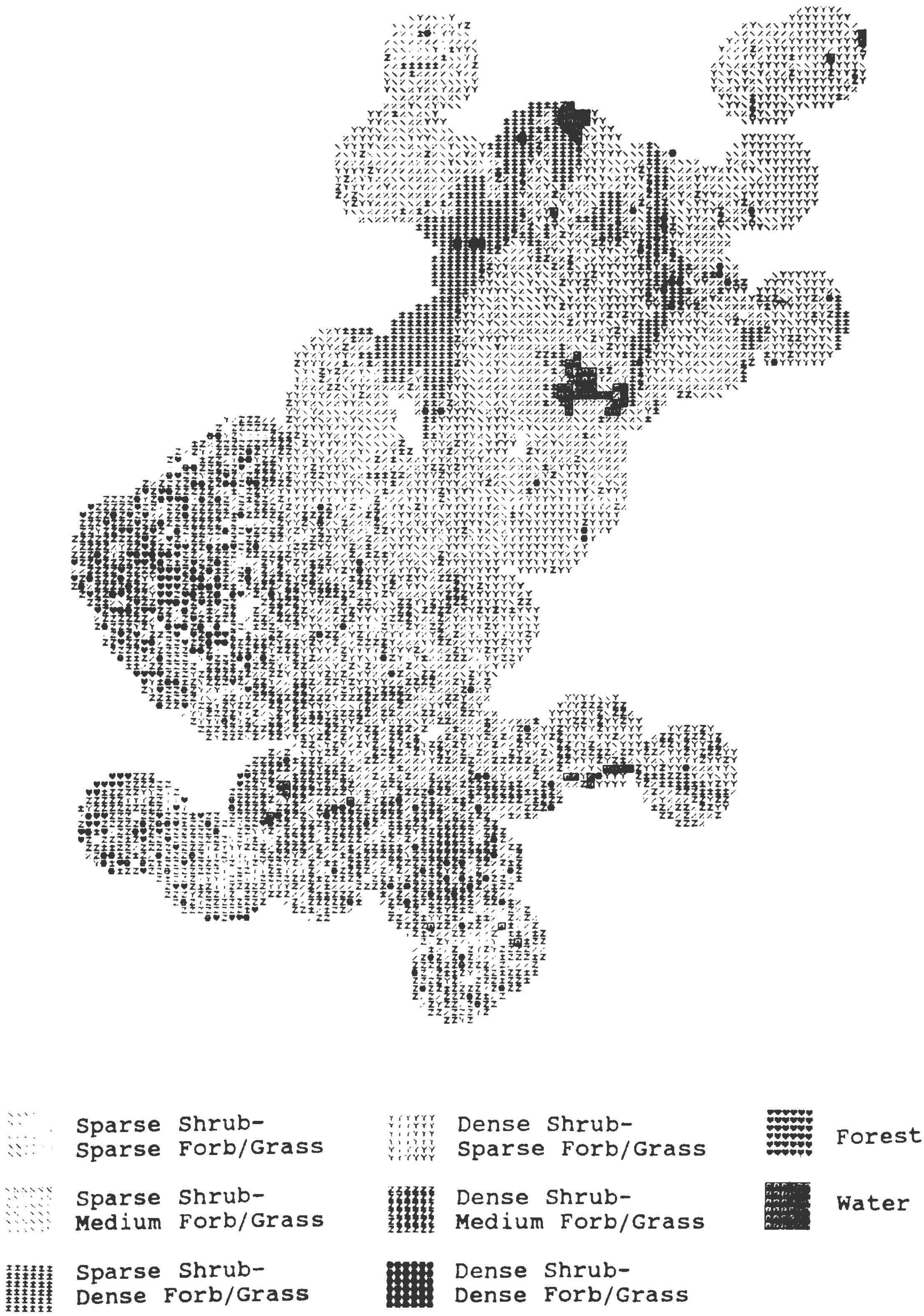


Figure 7. Analysis area formed from the digital creation of 54 pixel buffers around each sage grouse location within one study site. Scale = 1:200,000.

Table 7. Confusion matrix comparing generalized land cover classification derived from Landsat-5 TM digital data with classification derived from ground observations.

	Landsat Classes			
Ground Classes	Range	Forest	Water	Total
Range	248	6	3	257
Forest	1	15	3	19
Water	0	0	28	28
Total	249	21	34	304

	Omission Errors (%)	Commission Errors (%)	Correct (%)
Range	9/257 = 3.5	1/257 = 0.4	248/257 = 96.5
Forest	4/19 = 21.1	6/19 = 31.6	15/19 = 78.9
Water	0/28 = 0.0	6/28 = 21.4	28/28 = 100.0

Overall Accuracy = 291/304 = 95.7%

Table 8. Confusion matrix comparing the detailed range cover classification derived from Landsat-5 TM digital data with the classification derived from ground observations.

Ground Classes	Landsat Classes SS[a]	SM	SD	DS	DM	DD	F	W	Total
SS[a]	12	8	0	6	0	0	0		26
SM	5	12	2	6	7	0	0		32
SD	0	3	48	0	4	7	1		63
DS	1	4	0	22	25	0	3	3[b]	55
DM	0	10	2	8	42	2	0		64
DD	0	1	2	0	4	5	2		14
F	0	0	1	0	0	0	15	3	19
W	0	0	0	0	0	0	0	28	28
Total	18	38	55	42	82	14	21	34	301 + 3[b] = 304

	Omission[c] Errors (%)	Commission Errors (%)	Correct (%)
SS	14/26 = 53.8	6/26 = 23.1	12/26 = 46.2
SM	20/32 = 62.5	26/32 = 81.3	12/32 = 37.5
SD	15/63 = 23.8	7/63 = 11.1	48/63 = 76.2
DS	33/55 = 60.0	20/55 = 36.4	22/55 = 40.0
DM	22/64 = 34.4	40/64 = 62.5	42/64 = 65.6
DD	9/14 = 64.3	9/14 = 64.3	5/14 = 35.7
F	4/19 = 21.1	6/19 = 31.6	15/19 = 78.9
W	0/28 = 0.0	6/28 = 21.4	28/28 = 100.0

Overall Accuracy = 184/304 = 60.5%

[a]Cover classes are as follows: SS = Sparse Shrub-Sparse Forb/Grass, SM = Sparse Shrub-Medium Forb/Grass, SD = Sparse Shrub-Dense Forb/Grass, DS = Dense Shrub-Sparse Forb/Grass, DM = Dense Shrub-Medium Forb/Grass, DD = Dense Shrub-Dense Forb/Grass, F = Forest, W = Water.

[b,c]Three pixel groups belonging to various range classes were misclassified as water. No ground-truth information was gathered at these plots to identify which range classes were confused.

Use vs. Availability Analysis
--Cover Types

I analyzed use vs. availability of sage grouse feeding/loafing and nesting habitat from overlays of grouse locations (Tables 9-12). Most nest sites selected by grouse were located within the 30-39% range of canopy cover of dead/live shrub with 20-29% of overall cover contributed by sagebrush species. These findings agree with existing management recommendations for sage grouse nesting areas (Call and Maser 1985, Call 1979, Braun et al. 1977).

In this study, conditions associated with nest sites included low forb/grass cover (0-9%) and heavy shrub cover; hence, the dense dead/live shrub-sparse forb/grass cover type emerged as the type most often selected for nesting. While this supports Klebenow's (1969, 1970) finding of relatively low average coverage of herbaceous vegetation at nest sites, it is contrary to the findings of Rasmussen and Griner (1938) and Wallestad (1972). These researchers reported grouse preference for dense understories in nesting stands, presumably because understory vegetation provides concealment from avian predators and a more favorable microclimate.

Many studies have found greater brood use in areas with more open shrub canopies, i.e., average shrub coverage in the 0-30% range (Klebenow 1969, 1970, 1982; Martin 1970; Klott and Lindzey 1990). Sagebrush canopy coverage in these studies averaged 1.7-21% (Klebenow 1969, 1970, 1982;

Table 9 (a-f). Early season (April-June) selection of continuous image habitat variables by sage grouse broods, hens, cocks, and nests during 1986 and 1987, in Rich and Morgan Counties, Utah, and Uinta and Lincoln Counties, Wyoming.[a]

a. Live Shrub

% Cover	Broods ($\underline{n}$ = 166)[b]	Hens ($\underline{n}$ = 549)	Cocks ($\underline{n}$ = 252)	Nests ($\underline{n}$ = 152)
0 - 9	-	-	-	-
10 - 19	-	0	0	0
20 - 29	0	+	0	0
30 - 39	0	+	+	0
40 - 49	+	-	0	0
50 - 59	0	-	-	-
60 +	0	-	0	0

b. Dead/Live Shrub

% Cover	Broods ($\underline{n}$ = 166)	Hens ($\underline{n}$ = 549)	Cocks ($\underline{n}$ = 252)	Nests ($\underline{n}$ = 152)
0 - 9	-	-	-	-
10 - 19	-	0	0	0
20 - 29	0	+	0	0
30 - 39	0	+	+	+
40 - 49	+	0	0	0
50 - 59	0	-	-	0
60 +	0	-	0	0

[a]Chi-square analyses followed by Bonferonni confidence intervals (Neu et al. 1974, Byers et al. 1984); + = selected, 0 = not selected, - = avoided ($\underline{p}$ < .05), NS = non-significant (p ≥ .05).

[b]$\underline{n}$ = total number of pixels in habitat mosaics occupied by grouse. Number of grouse locations are as in Table 2.

Table 9, continued.

c. Sagebrush

% Cover	Broods (n = 166)	Hens (n = 549)	Cocks (n = 252)	Nests (n = 152)
0 - 9	-	-	-	-
10 - 19	0	0	0	0
20 - 29	0	+	+	+
30 - 39	0	0	0	0
40 - 49	0	0	0	0
50 - 59	0	-	-	-
60 +	0	-	0	0

d. Forb/Grass

% Cover	Broods (n = 166)	Hens (n = 549)	Cocks (n = 252)	Nests (n = 152)
0 - 9	0	+	0	+
10 - 19	0	-	0	-
20 - 29	0	-	0	0
30 - 39	-	0	-	0
40 - 49	-	0	-	-
50 +	-	-	-	-

e. Forb

% Cover	Broods (n = 166)	Hens (n = 549)	Cocks (n = 252)	Nests (n = 152)
0 - 9	NS	+	+	NS
10 +	NS	-	-	NS

Table 9, continued.

f. Bare Ground/Rock

% Cover	Broods (n = 166)	Hens (n = 549)	Cocks (n = 252)	Nests (n = 152)
0 - 9	0	-	0	0
10 - 19	+	-	0	-
20 - 29	0	0	+	0
30 - 39	0	+	0	+
40 - 49	0	0	-	0
50 - 59	0	0	-	0
60 - 69	-	-	0	0
70 - 79	-	-	0	-
80 +	0	0	0	0

Table 10 (a-f). Late season (July-Sept.) selection of continuous image habitat variables by sage grouse broods, hens, and cocks during 1986 and 1987, in Rich and Morgan Counties, Utah, and Uinta and Lincoln Counties, Wyoming.[a]

a. Live Shrub

% Cover	Broods (n = 794)[b]	Hens (n = 991)	Cocks (n = 385)
0 - 9	+	+	+
10 - 19	+	0	0
20 - 29	0	-	-
30 - 39	-	-	0
40 - 49	-	0	0
50 - 59	0	0	0
60 +	-	0	-

b. Dead/Live Shrub

% Cover	Broods (n = 794)	Hens (n = 991)	Cocks (n = 385)
0 - 9	+	+	+
10 - 19	+	0	0
20 - 29	0	-	-
30 - 39	-	-	-
40 - 49	-	-	0
50 - 59	0	0	0
60 +	-	0	-

[a]Chi-square analyses followed by Bonferonni confidence intervals (Neu et al. 1974, Byers et al. 1984); + = selected, 0 = not selected, - = avoided ($p < .05$), NS = non-significant ($p \geq .05$).

[b]n = total number of pixels in habitat mosaics occupied by grouse. Number of grouse locations are as in Table 2.

Table 10, continued.

c. Sagebrush

% Cover	Broods (n = 794)	Hens (n = 991)	Cocks (n = 385)
0 - 9	+	+	+
10 - 19	0	-	0
20 - 29	-	0	0
30 - 39	-	-	-
40 - 49	0	-	-
50 - 59	-	0	-
60 +	-	0	-

d. Forb/Grass

% Cover	Broods (n = 794)	Hens (n = 991)	Cocks (n = 385)
0 - 9	-	-	-
10 - 19	+	0	+
20 - 29	+	+	+
30 - 39	+	+	+
40 - 49	0	+	0
50 +	-	+	0

e. Forb

% Cover	Broods (n = 794)	Hens (n = 991)	Cocks (n = 385)
0 - 9	-	-	-
10 +	+	+	+

Table 10, continued.

f. Bare Ground/Rock

% Cover	Broods ($\underline{n}$ = 794)	Hens ($\underline{n}$ = 991)	Cocks ($\underline{n}$ = 385)
0 - 9	NS	+	+
10 - 19	NS	0	0
20 - 29	NS	0	0
30 - 39	NS	-	-
40 - 49	NS	0	-
50 - 59	NS	-	0
60 - 69	NS	0	-
70 - 79	NS	0	0
80 +	NS	-	0

Table 11 (a,b). Early (April-June) and late (July-Sept.) season selection of rangeland cover classes by sage grouse broods, hens, cocks, and nests during 1986 and 1987 in Rich and Morgan Counties, Utah, and Uinta and Lincoln Counties, Wyoming.[a]

a. Early Season

Class[b]	Broods (n = 171)[c]	Hens (n = 554)	Cocks (n = 252)	Nests (n = 152)
SS	0	0	-	0
SM	0	-	0	-
SD	-	-	-	-
DS	0	+	+	+
DM	+	-	0	0
DD	0	-	0	0
F	0	0	-	-
W	-	-	-	-

b. Late Season

Class	Broods (n = 814)	Hens (n = 1001)	Cocks (n = 396)
SS	0	-	-
SM	+	0	+
SD	+	+	+
DS	-	-	-
DM	0	-	0
DD	0	0	0
F	0	0	0
W	-	-	-

[a]Chi-square analyses followed by Bonferonni confidence intervals (Neu et al. 1974, Byers et al. 1984); + = selected, 0 = not selected, - = avoided (p < .05), NS = non-significant ($p \geq .05$).

[b]Cover classes are as follows: SS = Sparse Shrub-Sparse Forb/Grass, SM = Sparse Shrub-Medium Forb/Grass, SD = Sparse Shrub/Dense Forb/Grass, DS = Dense Shrub/Sparse Forb/Grass, DM = Dense Shrub/Medium Forb/Grass, DD = Dense Shrub/Dense Forb/Grass, F = Forest, W = Water.

[c]n = total number of pixels in habitat mosaics occupied by grouse. Number of grouse locations are as in Table 2.

Table 12 (a,b). Early (April-June) and late (July-Sept.) season selection of habitat diversity levels by sage grouse broods, hens, cocks, and nests during 1986 and 1987 in Rich and Morgan Counties, Utah, and Uinta and Lincoln Counties, Wyoming.

a. Early Season[a]

Habitat Diversity Value[b]	Grouse Category			
	Broods ($\underline{n}$ = 171)[c]	Hens ($\underline{n}$ = 554)	Cocks ($\underline{n}$ = 252)	Nests ($\underline{n}$ = 152)
1	-	+	NS	+
2	0	-	NS	-
3	0	0	NS	0
4	+	0	NS	0
5 +	-	0	NS	-

b. Late Season

Habitat Diversity Value	Grouse Category		
	Broods ($\underline{n}$ = 814)	Hens ($\underline{n}$ = 1001)	Cocks ($\underline{n}$ = 396)
1	-	0	-
2	0	-	0
3	+	0	+
4	+	0	0
5 +	0	0	0

[a]Chi-square analyses followed by Bonferonni confidence intervals (Neu et al. 1974, Byers et al. 1984); + = selected, 0 = not selected, - = avoided ($\underline{p}$ < .05), NS = non-significant ($\underline{p} \geq .05$).

[b]Number of habitat classes within a 3 x 3 pixel window centered on grouse location.

[c]$\underline{n}$ = total number of pixels in habitat mosaics occupied by sage grouse. Number of individual grouse locations are as in Table 2.

Martin 1970; Peterson 1970; Wallestad 1971; Klott and Lindzey 1990). While my late-season brood locations occurred disproportionately often in low-density shrubs (0-19% canopy coverage, 0-9% sagebrush canopy coverage), my early season brood locations were associated with overall shrub coverages of 40-49%. The discrepancy between this study and others may be due in part to differences in my handling of grouse locations. My method was unique in using a 3 x 3 pixel window, rather than a precise point to identify grouse locations.

Hens and cocks exhibited similar patterns of habitat use. Early-season hen observations were located more in shrub cover in the 20-39% range while cocks made greater use of the 30-39% range. Both sexes selected sagebrush canopies ranging from 20 to 29%. Schoenberg and Braun (1980) observed similar patterns in hens located between April 18 and July 1, the equivalent of my early season.

Succulent forbs are important in the diets of both adult and juvenile grouse. As summer progresses and forbs dessicate in lowland sagebrush stands, grouse typically move to moister sites at higher elevations or to natural meadows and alfalfa fields (Patterson 1952; Klebenow 1969, 1982; Savage 1969; Peterson 1970; Wallestad 1971; Wallestad et al. 1975; Call 1979; Call and Maser 1985). The results of my overlays of grouse locations on forb/grass and forb components suggest that grouse select areas having lower

forb/grass and forb cover in the early part of the season. At this time, broods are feeding largely on insects and adults on sagebrush. Grouse shifted to areas characterized by higher herbaceous cover and lower shrub cover during the late season, reflecting movement to meadow areas by birds of all ages and sexes.

Use vs. Availability Analysis --Habitat Diversity

Few studies have addressed sage grouse habitat diversity. Savage (1969) noted that grouse broods frequent meadow-sagebrush ecotones where they feed on ants. Klott and Lindzey (1990) reported a tendency of grouse broods to feed at the edges of large openings and to avoid the centers. Dunn and Braun (1986), in the only quantitative study of grouse habitat diversity relationships, found habitat interspersion to be one of the most important determinants of summer grouse habitat. They also noted greater grouse use close to habitat edges.

Results of my study indicate that broods used habitat mosaics having a higher diversity value than did early season adult hens and cocks. Early season hen locations were in completely homogeneous sites (diversity value = 1), as were nest locations. One possible explanation is that the hens which were observed feeding and loafing were nesting nearby.

I know of no other studies which have looked at heterogeneity of habitat in the vicinity of sage grouse

nest sites. Recent findings have linked habitat fragmentation and edges with increased nest predation in birds (Gates and Gysel 1978, Horkel et al. 1978, Wilcove 1985). The methods used in my study may be useful in studying relationships of sage grouse (or other species) nesting success to homogeneity of vegetation cover around nest sites.

SUMMARY AND MANAGEMENT IMPLICATIONS

The methods used here offer an alternative to conventional procedures for classifying vegetation, wildlife habitat, and identifying patterns of habitat use. Though sage grouse were the subject of this study, these methods may have wide application in management of rangeland resources.

I found it possible to efficiently and accurately characterize rangeland vegetation relating to sage grouse needs for cover and feeding. This information was used to analyze actual grouse location data. Apparent patterns of habitat selection and avoidance make good sense in light of the literature on sage grouse habitat relationships. The approach used to quantify habitat diversity from remotely sensed data, and the findings yielded relative to grouse locations, invite further investigation of habitat heterogeneity in relation to animal distribution and abundance.

A logical extension of this work would be to

extrapolate the site-specific habitat definition developed here to an entire management unit. Through digital image processing and GIS, it is possible to generate maps predicting location, quality, and abundance of habitats required by grouse to sustain their seasonal needs. Such information would be useful for resource managers in planning habitat improvement activities in the most cost-effective manner.

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